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Yang, Yi; Heijungs, Reinout

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COMMENTARY AND DISCUSSION ARTICLE

# On the use of different models for consequential life cycle assessment

**Yi Yang**[1] **· Reinout Heijungs**[2,3]

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**Abstract**
*Purpose* Consequential life cycle assessment (CLCA) studies how a system responds to a decision in question. There has been a growing body of CLCA studies in the last decade, with different models being incorporated from other fields, partly to compensate for the limitations of the conventional linear models used in LCA. As much as we welcome the use of new models in (C)LCA, here we provide a cautionary note on this trend by highlighting the restrictiveness of assumptions underpinning different models. And we point to a path forward for future CLCA studies.
*Methods* We review the model setup of, and major assumptions behind, two classes of models used in CLCA studies. One is linear models such as process- or input-output-based LCA, which have been conventionally used in LCA. And the other is nonlinear optimization models such as computable general equilibrium (CGE), which are increasingly being applied in CLCA studies. While the linear models rest on several assumptions such as fixed coefficients and unlimited supply of inputs, so do the nonlinear optimization models. Among others, CGE models assume rationality, the limitations of which have been increasingly revealed by findings of experimental and behavioral economics. We also discuss some of the foundational questions. Are LCA estimates verifiable or falsifiable? If not, then is LCA science? And is the traditional definition of science based on falsifiability suited for LCA and other disciplines studying complex systems?
*Results and discussion* Considering that (1) LCA studies the complex human environment system and model estimates or predictions are largely unverifiable and (2) different classes of models have different strengths and limitations, we make the following recommendations. For decision makers, particularly policy makers, we recommend evaluating estimates from different classes of models, as opposed to relying on a single class, for more robust decision support. Each model estimate or prediction can be taken as a point of evidence. If most estimates point to the same direction, the results would be considered strong evidence of what would happen. If, on the other hand, model estimates are scattered with no obvious patterns, the results would be considered inconclusive and thus more research is needed. For modelers, we recommend efforts be put into improving a model's predictive capability by, e.g., relaxing some of the unrealistic assumptions such as fixed input/output coefficients, 1:1 perfect displacement, and systemic optimization.
*Conclusions* Our main message is that mathematical sophistication does not necessarily equal improvement in model accuracy. Given the complexity of the human - environment system, the uncertainties of predicting the future, and the limitations of different models, a multi-model approach is entailed for more robust decision-making, and continuous effort is needed to improve model predictability.

**Keywords** Behavioral economics · Complex science · Computable general equilibrium · Consequential life cycle assessment · Falsifiability

Responsible editor: Mary Ann Curran

✉ Yi Yang
yyandgin@gmail.com

[1] CSRA Inc., 3170 Fairview Park Drive, Falls Church, VA 22042, USA

[2] Department of Econometrics and Operations Research, Vrije Universiteit Amsterdam, Amsterdam, The Netherlands

[3] Institute of Environmental Sciences, Department of Industrial Ecology, Leiden University, Leiden, The Netherlands

## 1 Introduction

Should I bike or drive to work if I am concerned about the global warming impacts? Given limited resources, how should the government allocate funding across public infrastructure, early child development, fundamental research, etc., if the aim is to maximize long-term economic growth? Be it a small personal decision or a complicated policy, the main principle underpinning the process of decision-making is consequentialism. It is a principle in ethics that can be condensed into the teleological maxim that "the end justifies the means." That is to say, whether we take an action should depend on what consequences it generates. If an action generates better consequences than any of its alternatives, it should be preferred. There are also other ethical principles, such as the deontological ethics, where conforming to duties and rules is more important than the results of the actions as such. But consequentialism is the most widely used in the public policy arena (Fischer and Miller 2006).

Consequential life cycle assessment (CLCA) embodies the essences of consequentialism (Ekvall et al. 2005). It studies how a system responds to a decision in question (Curran et al. 2005) and argues that the basis of the decision is the environmental consequences generated. CLCA has often been contrasted with the attributional approach (ALCA), which studies how processes are interconnected in a well-defined system without a decision or change taking place (Finnveden et al. 2009). Over the past decades, there has been a rapidly growing body of literature (Earles and Halog 2011) covering various aspects of CLCA from data requirements (Weidema et al. 1999) to system boundaries and allocation (Ekvall and Weidema 2004). In particular, many different models have been incorporated into LCA for consequential modeling (Hertel et al. 2010; Stasinopoulos et al. 2012; Plevin 2016), partly to compensate for the limitations of the conventional models used in LCA, such as process- and input-output-based (IO-based) LCA.

Here, we provide a cautionary note on this trend, by highlighting the restrictiveness of assumptions used in different classes of models. We focus on the conventional linear models such as process- and IO-based LCA, on the one hand, and nonlinear optimization models such as environmentally extended computable general equilibrium (CGE), on the other, within the context of consequential LCA. Process-based and IO-based models are what have been traditionally applied in LCA studies (Heijungs and Suh 2002). The reason we select CGE models is as follows. They have been increasingly incorporated into CLCA modeling (Earles and Halog 2011; Marvuglia et al. 2013). They are also the standard tool in economic analysis to study system-wide impacts of policy making or economic shocks (Dixon and Jorgenson 2012). Further, the assumptions behind CGE models reflect the very thinking of the mainstream neoclassic economics and are commonly shared by other economic models like partial equilibrium analysis. We seek to demonstrate that both classes of models are based on highly unrealistic assumptions that may undermine the accuracy and relevance of the results or predictions they generate. Finally, we point to a pathway forward for consequential modeling and decision-making. We acknowledge that our analysis is based on only two classes of models. This is not seen as a limitation because the CGE extension seems to be the most widely-used extension to traditional linear models in CLCA, and because we believe many of our points also pertain to other classes of models such as the Integrated Assessment Models (Pindyck 2013).

## 2 Linear production models: process-based and input-output-based LCA

For simplicity, we focus on process-based LCA here as IO-based LCA and hybrid LCA, which combine process-based and IO-based LCA (Suh and Huppes 2005), share a similar computational structure and assumptions when used to estimate changes. We first show in mathematical presentation that process-based LCA is a linear model and uses linear extrapolation to approximate changes. We then review what major assumptions are entailed in order for such linear extrapolation to work.

### 2.1 Computational structure

Process-based LCA is the default type of LCA that is advocated in the ISO standards (ISO 2006), even though no explicit equations are provided. The computational structure of process-based LCA is conventionally summarized by Heijungs and Suh (2002):

$$\mathbf{g} = \mathbf{B}\mathbf{A}^{-1}\mathbf{y} \tag{1}$$

where $\mathbf{A}$ is the technology matrix in which a column represents a process and a row a product, and elements of a column denote products consumed (in negative sign) or produced (in positive sign) by the process. $\mathbf{B}$ is the environmental matrix that records the quantity of emissions or natural resources emitted or consumed by processes in $\mathbf{A}$. $\mathbf{y}$ is a vector that denotes final demand related to the functional unit of a study, and $\mathbf{g}$ is the vector of life cycle emissions and resource extractions.

Equation (1) is commonly used in comparative studies to quantify the life cycle emissions of alternative technologies. This is done in some cases with a clear goal of promoting the ones estimated to have lower emissions or in other cases with implications that those with lower emissions should be produced more. Equation (1) is also commonly used to identify major contributors such as nitrogen fertilizers in crop production. This is done often with implications that, to continue with the crop example, reducing certain amount of nitrogen use would lead to a reduction of an equivalent amount of emissions estimated of nitrogen including both direct and embodied emissions.

In either use, we start with a situation (past, current, or future)

$$\mathbf{g}_0 = \mathbf{B}\mathbf{A}^{-1}\mathbf{y}_0 \tag{2}$$

where vector $\mathbf{y}_0$ usually has all zero components, except for the product being studied

$$\mathbf{y}_0 = \begin{pmatrix} 0 \\ \cdots \\ 0 \\ (y)_j \\ 0 \\ \cdots \\ 0 \end{pmatrix} \tag{3}$$

Next, we assume that a change takes place in demand, so that $\mathbf{y}_0$ is changed into $\mathbf{y}_1 = \mathbf{y}_0 + \Delta\mathbf{y}$. Assuming that matrices $\mathbf{A}$ and $\mathbf{B}$ are unchanged even though $\mathbf{y}$ changes, the process-based LCA predicts the consequences as follows:

$$\begin{aligned}\mathbf{g}_1 &= \mathbf{B}\mathbf{A}^{-1}\mathbf{y}_1 = \mathbf{B}\mathbf{A}^{-1}(\mathbf{y}_0 + \Delta\mathbf{y}) = \mathbf{B}\mathbf{A}^{-1}\mathbf{y}_0 + \mathbf{B}\mathbf{A}^{-1}\Delta\mathbf{y} \\ &= \mathbf{g}_0 + \mathbf{B}\mathbf{A}^{-1}\Delta\mathbf{y}\end{aligned} \tag{4}$$

where $\mathbf{g}_1$ represents the new emission level in a new situation following the decision in question and $\Delta\mathbf{y}$ represents additional production due to the decision. Hence, we find

$$\Delta\mathbf{g} = \mathbf{B}\mathbf{A}^{-1}\Delta\mathbf{y} \tag{5}$$

Clearly, the amount of impact change ($\Delta\mathbf{g}$) that is associated with a change in demand ($\Delta\mathbf{y}$) is a linear function of $\Delta\mathbf{y}$. We will refer to this as process-based LCA being a linear model. Note that the appearance of a matrix inverse implies nonlinear dependence on the elements of the technology matrix $\mathbf{A}$. So, the term "linear model" refers to a linear relation between cause ($\Delta\mathbf{y}$) and effect ($\Delta\mathbf{g}$). The same can be said of other major LCA models such as IO-based LCA and hybrid LCA (Yang 2017). Also note that the assumption of constant $\mathbf{A}$ and $\mathbf{B}$ is of course doubtful as to be discussed below, but it is a widely used practice, both in CLCA (Yang 2016) and in the Leontief IO-model for impact analysis (Miller and Blair 2009).

### 2.2 Assumptions and limitations

There are several major assumptions behind such linear models as process-based or IO-based LCA when they are used to estimate environmental consequences. The first assumption is that the model uses fixed input/output coefficients. For instance, if a refinery uses 0.2 kWh of electricity to produce 1 l of gasoline at the current output level, a decision to produce 1 additional liter of gasoline would use 0.2 kWh of electricity and a decision to produce 1000 additional liters of gasoline would use 200 kWh of electricity. There are no economies of scale or diseconomies of scale; there are no capacity effects, etc. The second assumption is infinite elastic supply of inputs, e.g., the assumption that an additional 1000 l of gasoline would use 200 kWh of electricity rests on a further assumption that there is enough supply of electricity (and of all the inputs used to generate electricity and so forth). The third assumption is that there is adequate market capacity to assimilate co-products, e.g., the decision to produce additional gasoline would result in additional output of other products such as diesel, and they are assumed to be adequately accommodated by the market without consequences in terms of prices, preferences, and market shares.

Under these assumptions, a process or industry consumes input materials and generates environmental emissions in fixed proportions, with no supply-side or demand-side constraints, and with no economies or diseconomies of scale, whatever the level of output is. In other words, changes estimated by linear models are a simple linear extrapolation from the initial situation modeled in the inventory. These assumptions can be highly unrealistic in certain circumstances and thus may fall short of decision support. A classic example is US corn ethanol, where early LCA studies applying the linear models (Farrell et al. 2006) failed to recognize the land constraint of corn production and thus significantly misestimated the potential consequences of corn ethanol expansion (Fargione et al. 2008; Searchinger et al. 2008). The use of linear models for CLCA modeling without recognizing their limitations and assumptions can be considered as what Manski describes as "wishful extrapolation" in policy analysis (Manski 2013). He defined it as "the drawing of a conclusion about some future or hypothetical situation based on observed tendencies and maintained assumptions" (Manski 2013). He pointed out that "Policy analysis is not just historical study of observed tendencies. A central objective is to inform policy choice by predicting the outcomes that would occur if past policies were to be continued or alternative ones were to be enacted" (Manski 2013).

## 3 Nonlinear optimization models: computable general equilibrium

Above, we have shown that the process-based and IO-based methods used traditionally in CLCA are linear models with respect to the demand of a product. We have also reviewed some of the major assumptions of these models that are highly unrealistic in certain circumstances. What these assumptions reflect is that linear models such as process-based and IO-based LCA portray the world in a mechanistic and stylized manner that ignores important characteristics of the market, such as substitution, price effects, elasticity of demand and supply, and rebound effects. Partly because of these limitations, scholars have turned to more sophisticated economic models such as computable general equilibrium (CGE) and partial equilibrium models, first within the economic domain (e.g., Rose 1995; Wing 2004; Dixon and Jorgenson 2012) but gradually also in the environmental domain, including CLCA modeling (Earles and Halog 2011; Vázquez-Rowe 2014). Interestingly, history seems to be repeating itself. Input-output analysis (IOA), the framework developed by Leontief (1941) and underpinning the IO-based LCA approach, used to be part of a mainstream tool in the economics literature but was gradually replaced by equilibrium models mainly because of the limitations (e.g., fixed coefficients, perfectly elastic supply and demand) discussed above. As we are to demonstrate, however, mathematical sophistication does not necessarily equal improved predictions (Krugman 2009). Below, we review the working and assumptions of GCE models, focusing on the essentials of the methodology. Equations below showing the computation structure of CGE models are derived from an introductory article by Wing (2004), to which readers of interest may refer for more details (see also (Burfisher 2011)). Part of our goal is to show how CGE models contrast with the linear models conventionally used in LCA.

### 3.1 Computational structure

CGE models are nonlinear optimization models building on three building blocks: consumer utility maximization, producer profit maximization, and market equilibrium. In the first building block, a representative consumer is assumed to maximize utility, $U$, by consuming a mix of $n$ commodities in quantities $y_1, \ldots, y_n$, subject to an income constraint, $m$, as shown below:

$$\begin{aligned} &\max U(y_1, \ldots, y_n) \\ &\text{subject to } m = \sum_{i=1}^{n} p_i y_i \end{aligned} \tag{6}$$

where $p_i$ indicates the price of commodity $i$. Note that for simplicity we assume the consumer does not save and spends all income on consumption. The utility function $U(\cdot)$ used in CGE models often takes the Cobb-Douglas form (Cobb and Douglas 1928) as in Eq. (7).

$$U = A y_1^{\alpha_1} y_2^{\alpha_2} \ldots y_n^{\alpha_n} \tag{7}$$

Here, $A$ is a scalar, and it is assumed that $\alpha_1 + \alpha_2 + \cdots + \alpha_n = 1$ (i.e., constant returns to scale, a commonly used assumption in CGE). Solving Eq. (6) and Eq. (7) yields that the share of commodity $i$ in expenditure on consumption equals $\alpha_i$.

The second building block is the assumption that each producer $j$ maximizes profit shown as below:

$$\begin{aligned} &\max \pi_j = p_j x_j - \sum_{i=1}^{n} p_j z_{ij} - \sum_{f=1}^{F} w_f v_{fj} \\ &\text{subject to } x_j = \phi_j(z_{1j}, \ldots, z_{nj}; v_{1j}, \ldots, v_{Fj}) \end{aligned} \tag{8}$$

where $\pi_j$ and $x_j$ denote the profit and output of producer $j$, $z_{ij}$ intermediate input from producer $i$ to producer $j$, $v_{fj}$ primary factor inputs $(1, \ldots, F)$ like labor and capital, and $w_f$ factor prices such as labor salary and capital gains. $\phi(\cdot)$ denotes the production function, which also in many cases takes a Cobb-Douglas form as shown in Eq. (9).

$$x_j = A_j \left( z_{1j}^{\beta_1} z_{2j}^{\beta_2} \ldots z_{nj}^{\beta_n} \right) \left( v_{1j}^{\gamma_1} v_{2j}^{\gamma_2} \ldots v_{Fj}^{\gamma_F} \right) \tag{9}$$

Again, in a Cobb-Douglas economy, it is assumed that $\beta_1 + \ldots + \beta_n + \gamma_1 + \ldots + \gamma_F = 1$, and $A_j$ is a scalar. Solving Eqs. (8) and (9) yields that $\beta_i$ and $\gamma_f$ equal the share of input $i$ and $f$ in total cost of sector $j$.

The third building block is equilibrium on all markets, which consists of commodity clearance, endowment balance, zero profit, and income balance. Commodity clearance means that the quantities of a commodity used (either as an intermediate input or consumed as final demand) must sum to the quantity produced by the economy (Eq. (10)). Endowment balance means that the quantities of a primary factor used by all sectors must sum to the economy's endowment of that factor ($V_f$, Eq. (11)). Zero profit means that the value of intermediate inputs and primary factors employed by a sector must sum to the value of the sector's output (Eq. (12)). And income balance means that the income of a consumer equals all payments she receives such as salary and capital gains (Eq. (13)).

$$x_i = \sum_{j=1}^{n} z_{ij} + y_i \quad (\text{for all } i) \tag{10}$$

$$V_f = \sum_{j=1}^{n} v_{fj} \quad (\text{for all } f) \tag{11}$$

$$p_j x_j = \sum_{i=1}^{n} p_j z_{ij} - \sum_{f=1}^{F} w_f v_{fj} \quad (\text{for all } j) \tag{12}$$

$$m = \sum_{f=1}^{F} w_f V_f \tag{13}$$

In summary, Eqs. (10) to (13) constitute the building blocks of CGE models as far as the economics is concerned. How the models operate is that they are first calibrated against a benchmark equilibrium, usually represented by an environmentally extended social accounting matrix (SAM), which is an expanded input-output table. In this step, technical coefficients ($z_{ij}$, $v_{fj}$) and elasticity parameters ($\alpha_i$, $\beta_j$, $\gamma_f$) of the utility and production functions can be estimated from the SAM.

Through an environmental extension, CGE models may further be used to study environmental impacts. Emissions, for example, can be connected with a producer's output level (Capros et al. 2013) such that the total amount of emission $k$ generated by all the productive sectors is calculated by

$$g_k = \sum_{j=1}^{n} b_{kj} x_j \tag{14}$$

In the context of CLCA, to study the environmental impacts of, for example, product promotion, one can first specify a new consumption level for the product/sector of interest and set it as an exogenous variable (a "shock"), and then rerun the model to solve for a new equilibrium. This would yield different results of use of endowments, prices, and sectoral outputs, hence different amounts of emissions. Comparing the new against the benchmark equilibrium with respect to emissions yields the impacts of the product promotion. Note that when a new exogenous variable is set that is different from those of the benchmark equilibrium, some other exogenous variable has to be endogenized to keep the model square. In CGE models, there is an equal number of exogenous and endogenous variables (see (Burfisher 2011) for details).

### 3.2 Assumptions and limitations

In comparison to linear models, CGE are much more mathematically sophisticated in representing market mechanisms. They "explicitly incorporate factor constraints, allow for input substitution and have a strong price-quantity integration" (Rose 1995). There are, however, notable limitations to CGE models. They typically represent an economy in 30–50 sectors (Burfisher 2011), a resolution much more aggregate as opposed to process- or IO-based models. Many of the parameters in environmentally extended CGE models are more reliant on expert judgements and assumptions than on empirical observations (Babcock 2009). Also, the models rely on the choice of special functional forms (such as Cobb-Douglas) to ensure the existence of and stability of equilibrium (Barker 2004). Finally, the principles for estimating the environmental coefficients are inconsistent with that for the inputs from markets. For a more detailed critique of CGE models, see (Barker 2004).

An additional point of fundamental importance is that CGE models are rooted in the neoclassical economic assumptions, the limitations of which have been increasingly recognized (Thaler 2015). As reflected in some of the building blocks, neoclassical economics assumes that individuals have rational expectations and maximize utility and firms maximize profits, both with perfect information (Colander 2000), and that markets clear, so there is no surplus or shortage of products, labor, land, etc. In other words, in neoclassic economics human beings are assumed to be highly intelligent and always make perfectly rational choices that are the best for them, while markets and institutions function perfectly well.

But these are profoundly unrealistic assumptions as the real human beings are very irrational or un-neoclassical as reveled by the development of behavioral economics over the past few decades (Sen 1977; Ariely 2009; Thaler 2015). For example, if we were what neoclassic economics assumes, we would need no advertisement, we would have no obesity, we would encounter no economic crises or recessions, and we would not offer a beer to a friend. But the real world begs to differ, and we are still straining to climb out of the current economic recession from the 2008 financial crisis, which few economic models had predicted (Krugman 2009). Building on strong assumptions unreflective of the real world, therefore, the CGE models may fall short of an adequate basis for decision-making. Such limits have been identified in critiques on neo-classical economics, and it has led to many new developments, from bounded rationality (Simon 1957; Sen 1977) to the booming fields of neuro-economics, behavioral economics, and experimental economics (Camerer et al. 2005, 2011).

## 4 A path forward for CLCA and decision-making

As shown above, both linear models such as process and IO LCA and nonlinear-optimization models can be used for CLCA modeling, but both are based on highly restrictive assumptions. Besides the two major classes of models reviewed above, there are yet other models used for CLCA modeling. They include nonlinear models such as system dynamics and integrated assessment models (IAMs) (Dowlatabadi 1995; Stasinopoulos et al. 2012) and linear optimization models (Duchin and Levine 2011). These models may also rest on strong assumptions (see, e.g., Pindyck 2013 for a critique of IAMs).

Given that different classes of models have different strengths and limitations, we recommend evaluating their collective results, as opposed to relying on a single class of models, as indication of what would occur as a result of the decision in question. This is especially relevant for policy makers as policies generally have large economic and environmental consequences. If different classes of models speak the same language, meaning that model predictions are concentrated, the results would be strong evidence of what would occur (outcome 3, Fig. 1). If, on the other hand, model predictions are spread out with no obvious patterns, the results would be considered inconclusive and thus more research is needed (outcome 1, Fig. 1). In this case, it is more scientific to admit partial or no knowledge than to create false certitude (Manski 2013).

And outcome 1, where model predictions are widely spread out around 0, shows that a conclusion may not be reached based on current knowledge, hence more research needed.

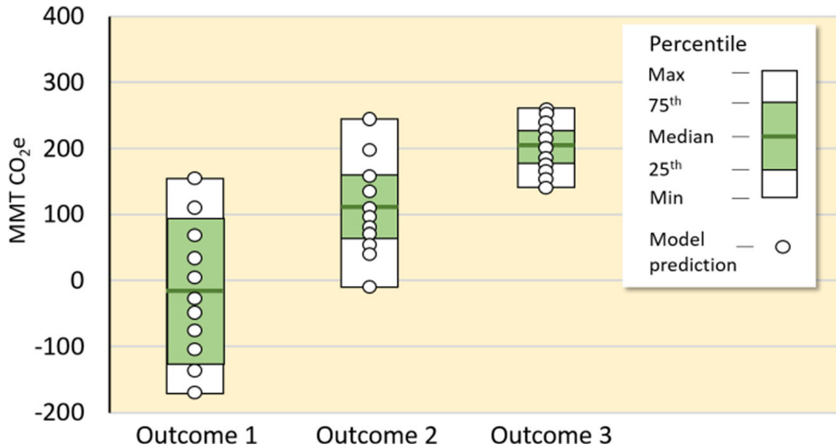


**Fig. 1** A hypothetical example of evaluating the climate impact of a policy using a suite of models from different classes, with three possible outcomes. Outcome 3, where model predictions are concentrated, provides strong evidence that the policy would increase GHG emissions by around 160–200 million metric tons (MMT) of $CO_2e$. Outcome 2, where model predictions are somewhat concentrated, provide weak evidence that the policy would increase GHG emissions by 70–150 MMT $CO_2e$ but strong evidence that the policy would worsen climate change

The reasons behind the recommendation are twofold. First, from a behavioral perspective, in the linear models we reviewed, agents basically repeat what they did before, while in the nonlinear optimization model agents are perfectly rational and capable of always making the optimal decisions. Neither of the models is an adequate representation of the reality (Thaler 2015) but each probably captures parts of it. This is why we believe using the collective estimates of different models may be more likely to predict the future than relying on the estimates of a single model.

Second, as with many other disciplines, LCA studies a complex system and is limited by our ability to conduct controlled experiments. As a result, estimates of LCA are in most practical cases unverifiable or unfalsifiable (Oreskes et al. 1994; Babcock 2009). For example, how would we go about testing the prediction that an increased used of 1 million electric cars would reduce GHG emissions by *x* million tons a year? The fact of the matter is that we simply cannot. According to the Popper's definition of science based on falsifiability (Popper 1959), LCA may be deemed unscientific. And so may many other scientific endeavors, including climate change (see below). But there are good reasons to reject Popper's definition of science when it comes to studying complex systems. The late climate scientist Stephen Schneider drove the point home in a series of talks on if the science of climate change is settled enough for policy (Schneider 2008):

> "…Falsification is a false doctrine. Falsification is appropriate in classical science, physics and chemistry. Now what's the probability that this is an acid or a base? [He holds up a cup of water and takes a sip.] I don't trust this test. What could I do? I could take a piece of litmus paper, put it in there. Red or blue, it absolutely would falsify a false hypothesis or reinforce it. When you have a complex system science, you have no idea if the new data that's collected has been collected right, you don't know whether it's meaningful, you don't know whether what was left out would trump the conclusion. Complex science is built on preponderance, built over long time…"

Schneider stressed the idea of preponderance of evidence as a means of settling science for policy making. Our recommendation of evaluating the collective results of a suite of models for decision-making is in the same spirit. And the point Schneider was making in the talk is that although estimates for complex systems may be ultimately unfalsifiable, research into various aspects of a system and carried out over time with continually improved data, modeling, or knowledge may improve the robustness of the results and greatly strengthen our confidence in the conclusions reached (e.g., climate change). Similar arguments have been raised in connection to "post-normal science" (Funtowicz and Ravetz 1990), which explicitly incorporates the idea that scientific analysis of complex societal questions necessarily includes values, choices, and uncertainties, and therefore needs a plurality of approaches.

This leads us to our second recommendation. Considering the unrealistic assumptions different models rest on, we strongly recommend that efforts be directed to improve a model's predictive capability by relaxing some of the restrictive assumptions. As different models become better reflective of the reality and at prediction, the range of estimates is likely to narrow, with the results more robust for decision-making (Fig. 2). For linear models like process- and IO-based LCA, for example, instead of simple linear extrapolation, scenarios can be built that better approximate the actual consequences of decision-making (Yang 2016). One can derive marginal coefficients, beyond average data, to model the processes to be affected (Weidema 2003; Sandén and Karlström 2007; Mathiesen et al. 2009; Weidema et al. 2013; Yang and Suh

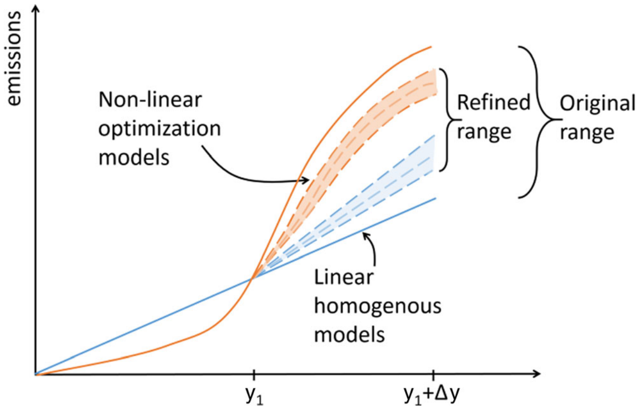


**Fig. 2** A hypothetical example of how relaxing model assumptions may narrow the range of collective estimates. The *solid lines* represent estimates from standard linear (blue) and nonlinear optimization (orange) models. *Dashed lines* represent improved estimates by relaxing some of the assumptions. $y_1$ indicates current demand and Δy additional demand resulting from the decision in question

2015). One can also incorporate partial equilibrium analysis or econometric methods to estimate a more realistic displacement ratio that considers market responses than the perfect 1:1 displacement ratio often assumed in LCA studies (e.g., 1 MJ of bioenergy displacing 1 MJ of fossil energy) (Zink et al. 2016).

All models could benefit from the insights of the developing experimental, behavioral, or neuro-economics (Camerer et al. 2005, 2011) such that more behaviorally enlightened models can be created. Instead of rationality with perfect information, for example, individuals and institutions base their decision on simple heuristics with limited information (Gigerenzer and Gaissmaier 2011). Also, firms seem to maximize sales rather than profits (Thaler 2015). These insights can be incorporated into CGE-type models to improve their estimates. A challenging question is how many different models or estimates would be needed to ensure convergence or divergence of results. The answer may depend on a range of factors including study scope: application in a multi-billion investment plan will pose stronger requirements than application in smaller projects. This question may be investigated in future CLCA studies. Ours is not a fully elaborated research protocol, but a theoretical story turned into a partial practical proposal, and experience must tell us how to apply it in concrete situations.

The path we point to clearly entails multi-, inter-, or transdisciplinary collaborations (Pohl 2005). An excellent example of the sort is a recent study (Stanford 2013), which used a dozen of different models developed by a range of institutes with different strengths and assumptions to evaluate the economic and environmental impacts of shale gas. Another good example is Plevin et al. (2010), who evaluated several different models in studying the uncertainty of the indirect land use change effect of biofuels expansion.

This multi-model proposal, however, does not necessarily mean that modelers should always include all the classes of models available on the market in one study. From a practical point of view, we may explore a couple of classes at a time. A recent study, for example, used a simple approach and a partial equilibrium model to quantify the climate impact of increasing production of water treatment chemicals in Australia (Alvarez-Gaitan et al. 2014). And for some research questions involving small changes, certain simple models may suffice because more sophisticated models would roughly arrive at the same results (West 1995). We can also focus on improving the predictive capability of a particular class of model. In this case, decision-makers are recommended to assemble and evaluate results from different studies using different models to determine the environmental consequences of a given decision.

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